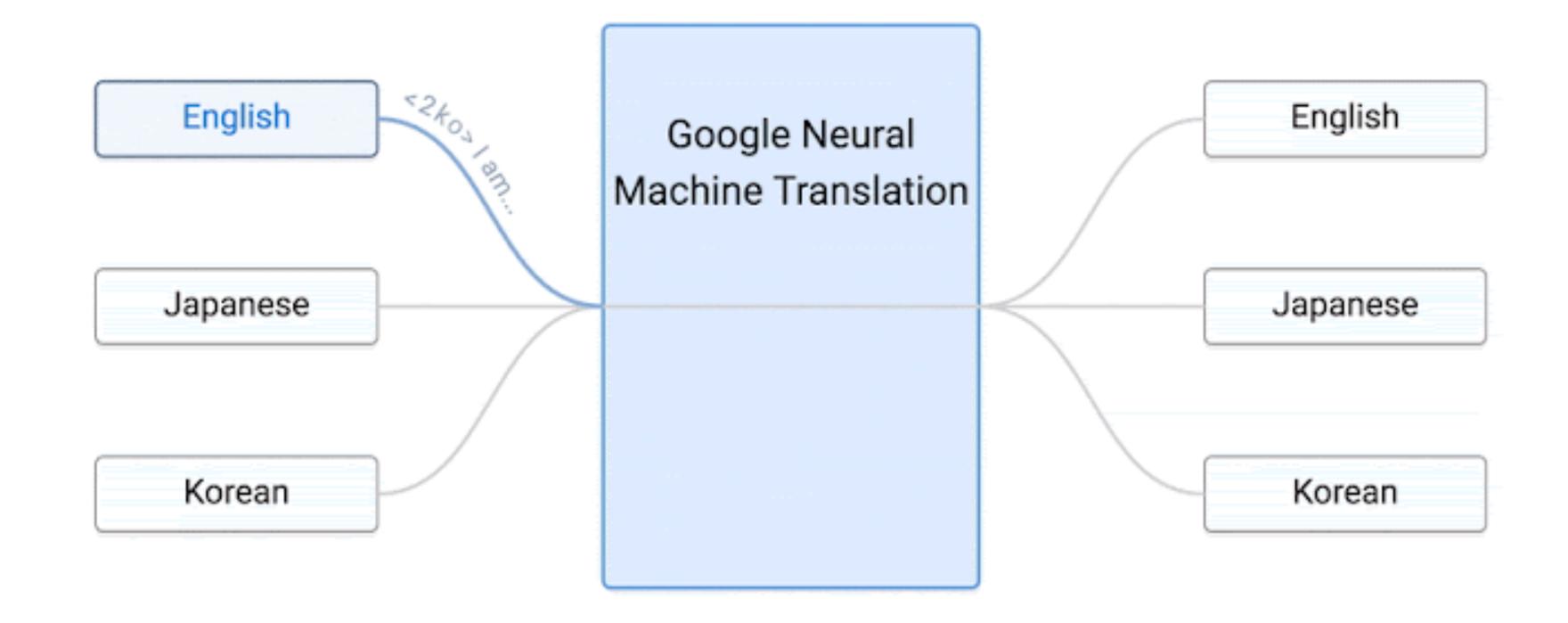
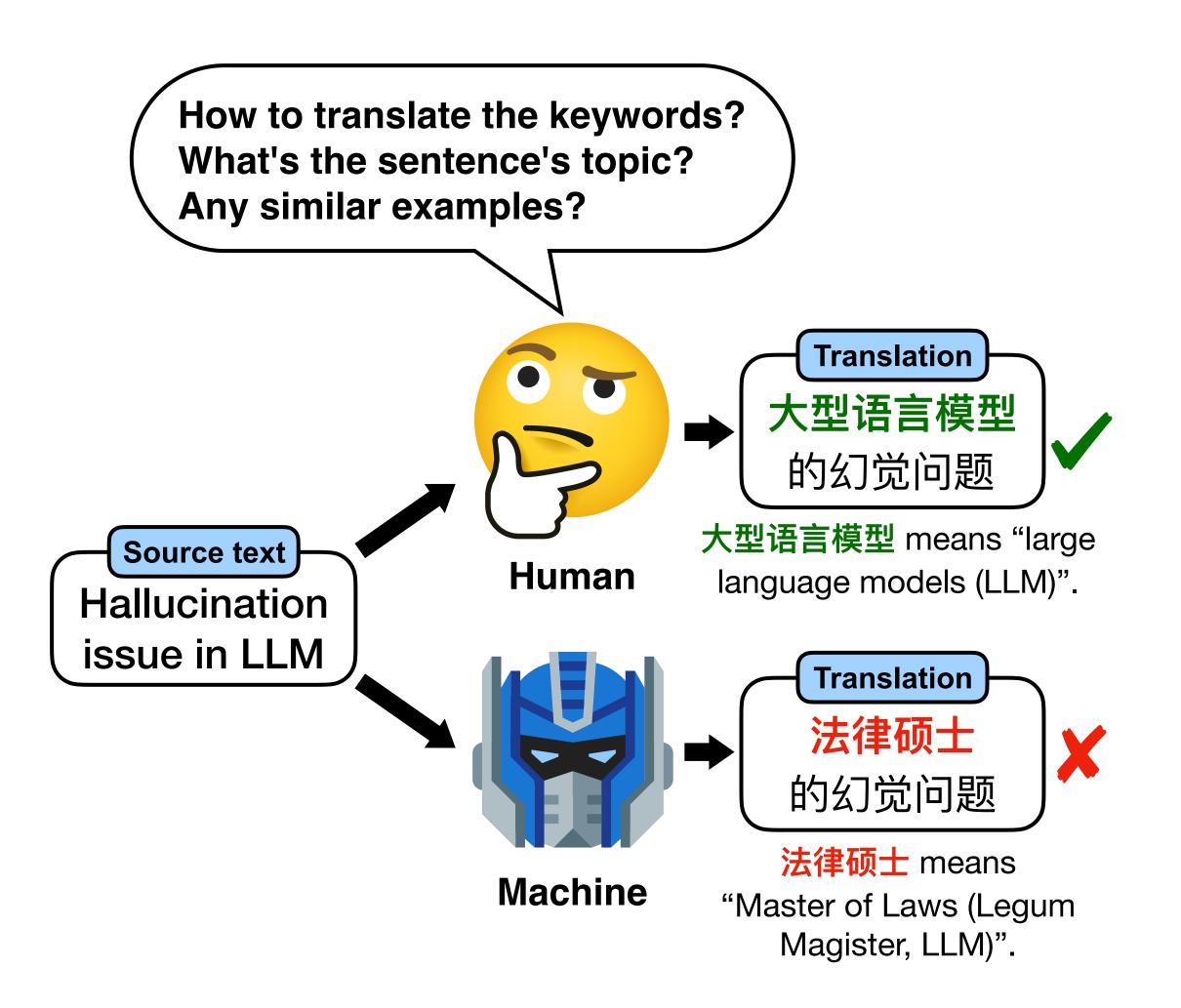
Exploring Human-Like Translation Strategywith Large Language Models

Traditional training process of NMT

Training



Machine v.s. Human translation



- NMT models are trained to perform source-to-target mapping.
- A human translator can take preparatory steps to ensure highquality translation.

Human-like strategies in LLM

Let's think step by step, ...

Chain-of-Thought

Let me do a reflection and think about how to improve my strategy, ...

Reflexion

Let's take a step back and generate a more generic question, ...

Step-Back prompting

Exploring Human-Like Translation Strategy with LLM



How to translate the keywords?

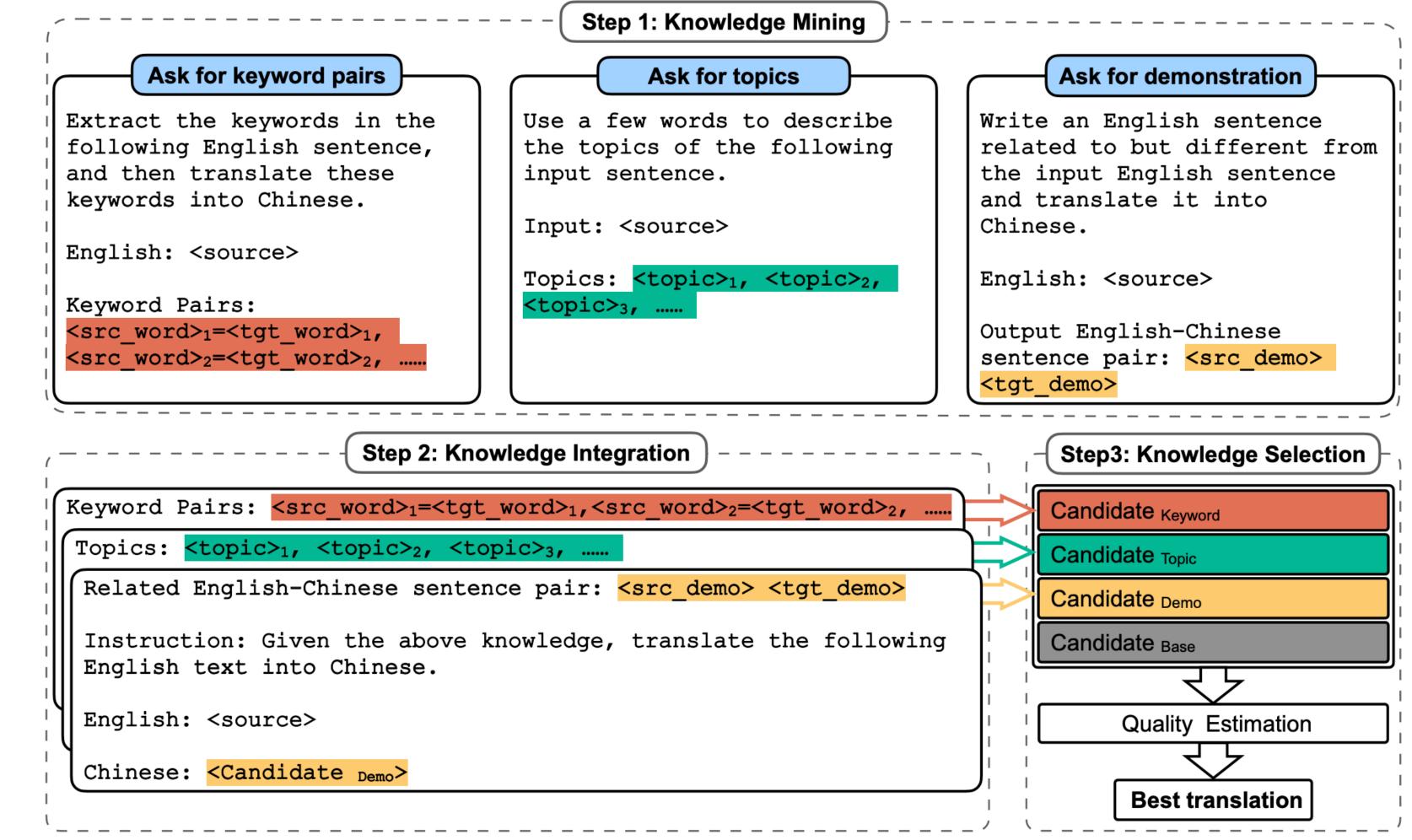
What's the sentence's topic?

Any similar examples?

- √ Identify keywords and consider how to translate them
- √ Reflect on what the main topic of this text is
- √ Consider how similar sentences (demonstrations) are translated.
- **√**

MAPS: Multi-Aspect Prompting and Selection

Prompting



MAPS: Multi-Aspect Prompting and Selection

Selection (or reranking)

• **LLM-SCQ**: Composing a single choice question (SCQ) that asks the LLM to choose the best candidate on its own.

• **COMET-QE:** A trained quality estimation (QE) scorer that assigns a numerical score to each candidate. Selection is based on the highest score.

• **COMET** (oracle): A reference-based scorer that assigns a numerical score to each candidate. It can be considered as the oracle QE method, representing the upper bound of selection.

Experiment setting

Comparative methods

- Baseline: standard zero-shot translation with temperature set to 0.
- *Rerank*: we randomly sample three times (temperature=0.3) and add *Baseline* to form four candidates. The best candidate is selected through QE.

Base model

• Text-davinci-003, Alpaca, Vicuna

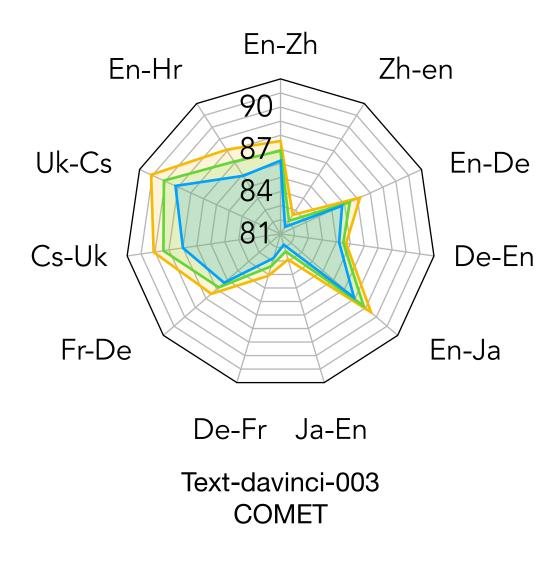
Metrics

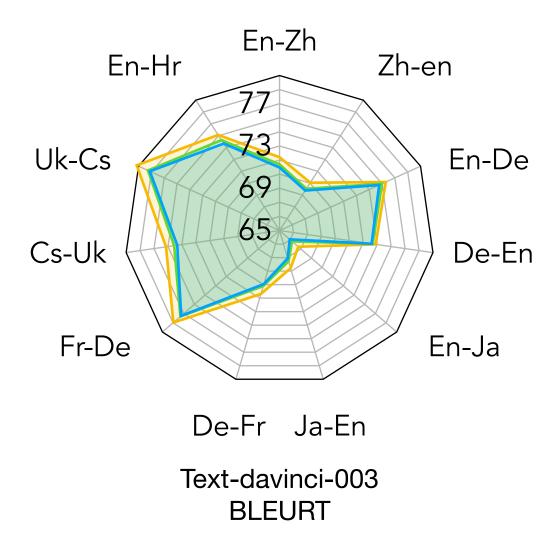
COMET and BLEURT

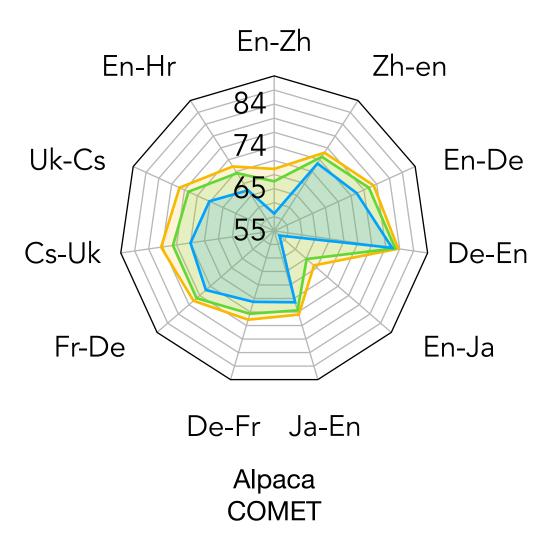
Testsets

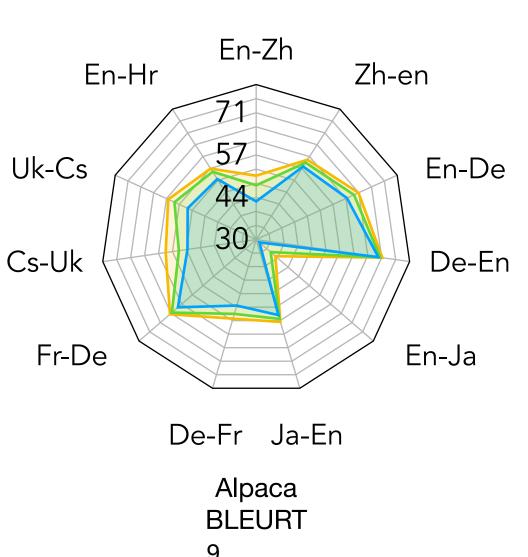
11 language pairs in WMT22

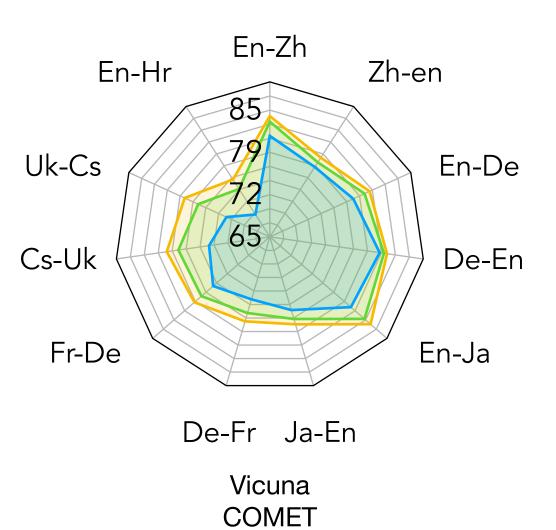
Main results







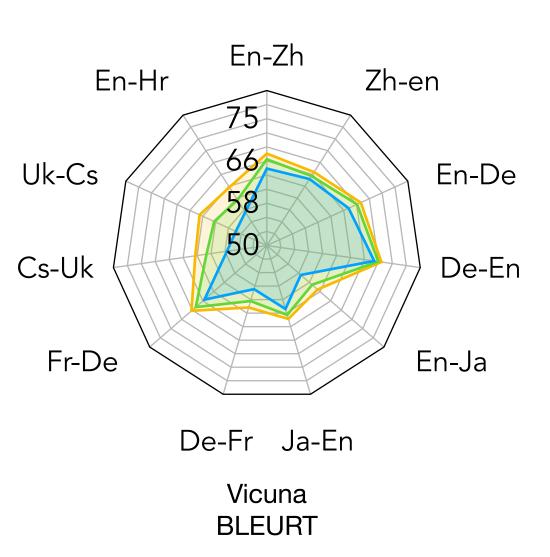




Rerank

MAPS

Baseline



Main results

Method	En-Zh	Zh-En	En-De	De-En	En-Ja	Ja-En	De-Fr	Fr-De	Cs-Uk	Uk-Cs	En-Hr
				T22 Bes	•	MET					
WMT22 Best	86.8	81.0	87.4	85.0	89.3	81.6	85.7	89.5	91.6	92.2	88.4
text-davinci-003 COMET											
Baseline 5-Shot (Hendy et al.)	86.2 87.0	81.6 81.1	85.8 86.5	85.2 85.2	87.9 88.2	81.8 82.0	82.8 83.6	86.3 86.6	88.0	89.2	85.9
									00.2	90.4	96.2
Rerank _{LLM-SCQ} MAPS _{LLM-SCQ}	86.4 86.8	81.7 82.0	86.0 86.4	85.2 85.4	88.0 88.5	82.0 82.4	83.0 83.4	86.4 86.9	88.3 88.8	89.4 89.9	86.3 86.5
Rerank COMET-QE	86.9	82.1	86.4	85.5	88.8	82.3	83.4	86.8	89.4	90.1	87.1
MAPS COMET-QE	87.6	82.6	87.2	85.7	89.5	82.9	84.1	87.5	90.1	91.1	88.1
↑ Rerank _{COMET}	87.5	82.6	86.9	85.8	89.3	82.3	83.4	86.8	89.9	90.7	87.7
$\overline{\uparrow}$ MAPS $_{\mathrm{COMET}}$	88.5	83.8	88.0	86.7	90.3	82.9	84.1	87.5	90.9	92.0	89.0
text-davinci-003 BLEURT											
Baseline	71.1	69.6	75.6	74.0	66.3	67.8	70.4	77.6	75.0	78.8	75.0
5-Shot (Hendy et al.)	72.2	69.2	76.3	74.5	67.1	68.0	70.9	78.0			
Rerank LLM-SCQ	71.4	69.8	75.9	74.1	66.6	68.1	70.6	77.7	75.3	79.0	75.4
MAPS LLM-SCQ	72.1	70.5	76.3	74.4	67.4	68.8	71.4	78.6	76.1	80.2	76.0
Rerank COMET-QE MAPS COMET-QE	71.7 72.6	70.1 70.8	76.1 77.1	74.3 74.6	67.3 68.3	68.3 69.1	71.2 71.9	78.1 78.9	76.4 77.4	79.7 81.2	75.9 77.1
↑ Rerank COMET ↑ MAPS COMET	72.4 74.0	70.6 72.1	76.5 77.8	74.6 75.7	68.0 69.4	68.8 70.9	71.8 73.6	78.6 80.2	76.8 78.3	80.2 82.1	76.4 77.9
MARS COMET											
Baseline	58.9	73.1	75.5	81.9	56.6	71.8	71.7	75.4	74.1	71.1	65.9
Rerank COMET-QE	66.2	74.9	78.5	82.6	64.7	73.7	74.5	78.2	78.1	76.3	70.5
MAPS COMET-QE	69.0	76.0	79.7	83.3	66.9	74.7	75.9	79.1	80.8	78.5	72.3
				Alpac	a BI	EURT					
Baseline	42.3	58.0	62.2	69.8	31.4	55.4	52.2	63.4	52.4	54.3	53.2
Rerank COMET-QE	47.5	59.5	64.7	70.4	36.2	56.7	55.0	66.0	55.2	59.0	56.0
MAPS COMET-QE	50.6	60.6	66.3	71.1	38.2	57.7	56.6	66.8	59.5	61.2	57.2
Dagalia -	01.2	70.4	70.0	Vicur	•	MET	75.5	77.1	74.0	70.7	60.2
Baseline	81.3	78.4	79.8	82.9	82.3	77.3	75.5	77.1	74.9	72.7	69.3
Rerank COMET-QE	83.6 84.5	79.3	81.8	83.6	85.2	78.8 70.7	77.8	79.6	79.9	77.7	74.2
MAPS COMET-QE	84.5	80.2	82.7	84.1	86.5	79.7	79.2	81.1	81.8	80.1	76.0
Baseline	64.9	65.3	67.4	Vicur 71.0	na BI 58.7	EURT 62.8	58.8	66.0	57.8	56.6	57.7
Rerank COMET-QE	66.7	66.0	69.2	71.8	61.6	64.0	61.2	68.2	61.8	61.2	60.5
MAPS COMET-QE	67.8	66.9	70.0	72.4	63.0	64.8	62.5	69.3	64.0	64.3	63.4
V											

- Using the same knowledge selection method, MAPS outperforms Rerank consistently.
- This indicates that the improvements brought by MAPS stem from three types of translationrelated knowledge:
 - keywords
 - topics
 - relevant demonstrations.

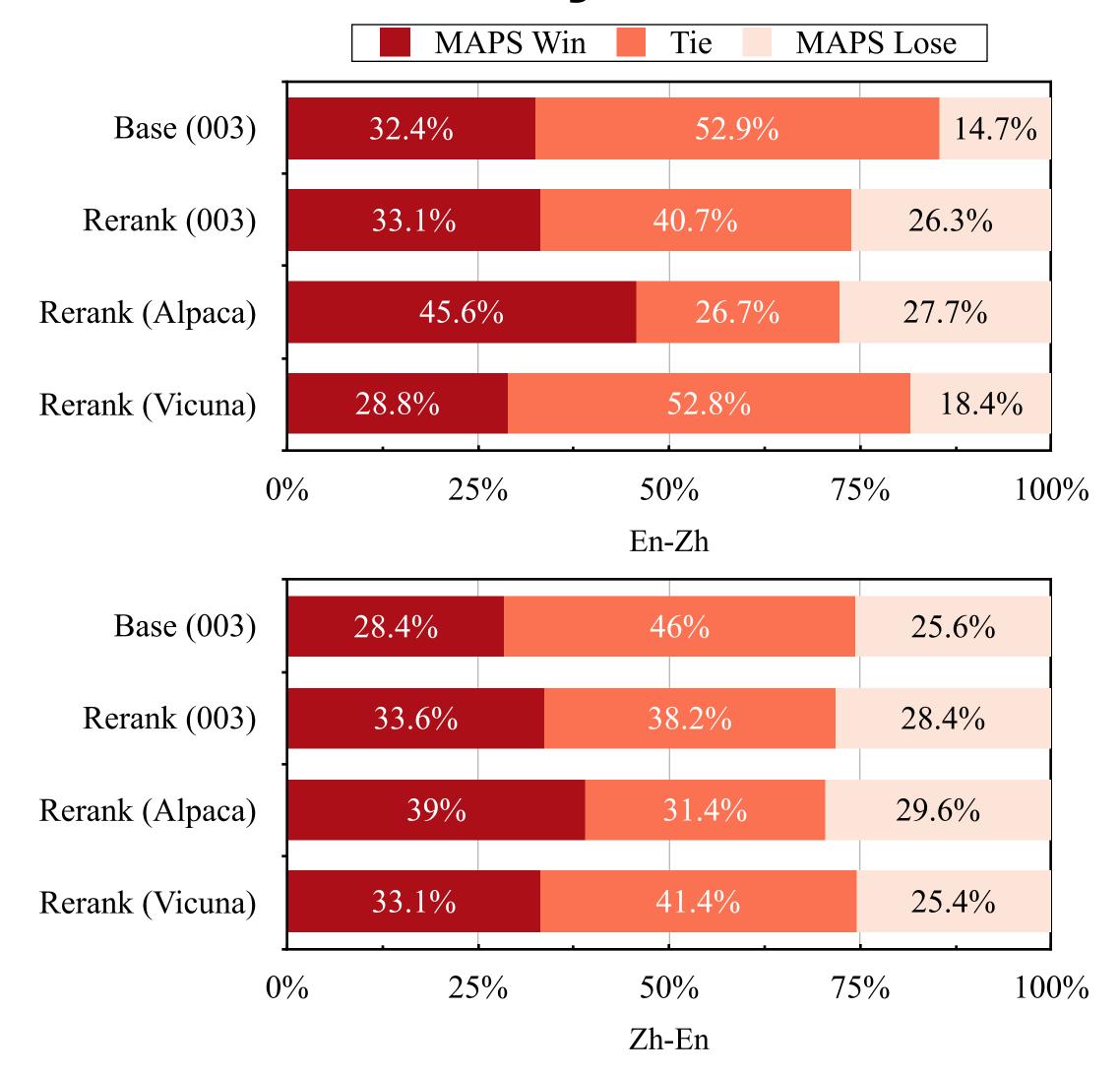
Main results

Method	En-Zh	Zh-En	En-De	De-En	En-Ja	Ja-En	De-Fr	Fr-De	Cs-Uk	Uk-Cs	En-Hr
	0.4.0	24.2		T22 Bes	•	MET		~~ ~	24.6		20.4
WMT22 Best	86.8	81.0	87.4	85.0	89.3	81.6	85.7	89.5	91.6	92.2	88.4
D V	06.2		xt-dav		-	MET	02.0	06.2	00.0	00.2	05.0
Baseline 5-Shot (Hendy et al.)	86.2 87.0	81.6 81.1	85.8 86.5	85.2 85.2	87.9 88.2	81.8 82.0	82.8 83.6	86.3 86.6	88.0	89.2	85.9
									00.2	90.4	96.2
Rerank _{LLM-SCQ} MAPS _{LLM-SCQ}	86.4 86.8	81.7 82.0	86.0 86.4	85.2 85.4	88.0 88.5	82.0 82.4	83.0 83.4	86.4 86.9	88.3 88.8	89.4 89.9	86.3 86.5
	86.9	82.1	86.4	85.5	88.8	82.3	83.4	86.8	89.4	90.1	87.1
Rerank COMET-QE MAPS COMET-QE	87.6	82.6	87.2	85.7	89.5	82.9	84.1	87.5	90.1	90.1 91.1	88.1
↑ Rerank COMET	87.5	82.6	86.9	85.8	89.3	82.3	83.4	86.8	89.9	90.7	87.7
↑ MAPS COMET	88.5	83.8	88.0	86.7	90.3	82.9	84.1	87.5	90.9	92.0	89.0
		te	xt-dav	inci-00)3 BI	EURT					
Baseline	71.1	69.6	75.6	74.0	66.3	67.8	70.4	77.6	75.0	78.8	75.0
5-Shot (Hendy et al.)	72.2	69.2	76.3	74.5	67.1	68.0	70.9	78.0			
Rerank $_{LLM ext{-}SCQ}$	71.4	69.8	75.9	74.1	66.6	68.1	70.6	77.7	75.3	79.0	75.4
MAPS _{LLM-SCQ}	72.1	70.5	76.3	74.4	67.4	68.8	71.4	78.6	76.1	80.2	76.0
Rerank COMET-QE	71.7	70.1	76.1	74.3	67.3	68.3	71.2	78.1	76.4	79.7	75.9
MAPS COMET-QE	72.6	70.8	77.1	74.6	68.3	69.1	71.9	78.9	77.4	81.2	77.1
Rerank COMET	72.4	70.6	76.5	74.6	68.0	68.8	71.8	78.6	76.8	80.2	76.4
↑ MAPS COMET	74.0	72.1	77.8	75.7	69.4	70.9	73.6	80.2	78.3	82.1	77.9
Development	50.0	70.1	75.5	Alpac		MET	71.7	75.4	74.1	71.1	(5.0
Baseline	58.9	73.1	75.5	81.9	56.6	71.8	71.7	75.4	74.1	71.1	65.9
Rerank COMET-QE	66.2	74.9	78.5	82.6	64.7	73.7	74.5	78.2	78.1	76.3	70.5
MAPS COMET-QE	69.0	76.0	79.7	83.3	66.9	74.7	75.9	79.1	80.8	78.5	72.3
Dagalina	40.2	50.0	62.2	Alpac	•	EURT	50.0	62.4	52.4	54.2	52.2
Baseline	42.3	58.0	62.2	69.8	31.4	55.4	52.2	63.4	52.4	54.3	53.2
Rerank COMET-QE MAPS COMET-QE	47.5 50.6	59.5 60.6	64.7 66.3	70.4 71.1	36.2 38.2	56.7 57.7	55.0 56.6	66.0 66.8	55.2 59.5	59.0 61.2	56.0 57.2
TAKE 5 COMET-QE	30.0	00.0	00.5				20.0	00.0	37.3	01.2	31.2
Baseline	81.3	78.4	79.8	Vicur 82.9	na CC 82.3	77.3	75.5	77.1	74.9	72.7	69.3
						78.8					
Rerank COMET-QE MAPS COMET-QE	83.6 84.5	79.3 80.2	81.8 82.7	83.6 84.1	85.2 86.5	79.7	77.8 79.2	79.6 81.1	79.9 81.8	77.7 80.1	74.2 76.0
COMET-QE				Vicur		EURT			3		
Baseline	64.9	65.3	67.4	71.0	58.7	62.8	58.8	66.0	57.8	56.6	57.7
Rerank COMET-QE	66.7	66.0	69.2	71.8	61.6	64.0	61.2	68.2	61.8	61.2	60.5
MAPS COMET-QE	67.8	66.9	70.0	72.4	63.0	64.8	62.5	69.3	64.0	64.3	63.4
MIAI S COMET-QE	07.0	00.9	70.0	72.4	03.0	04.0	02.5	09.3	04.0	04.3	03.4

• MAPS exhibits a higher upper bound for selection.

Human evaluation

Preference study



MAPS is generally more preferred by humans.

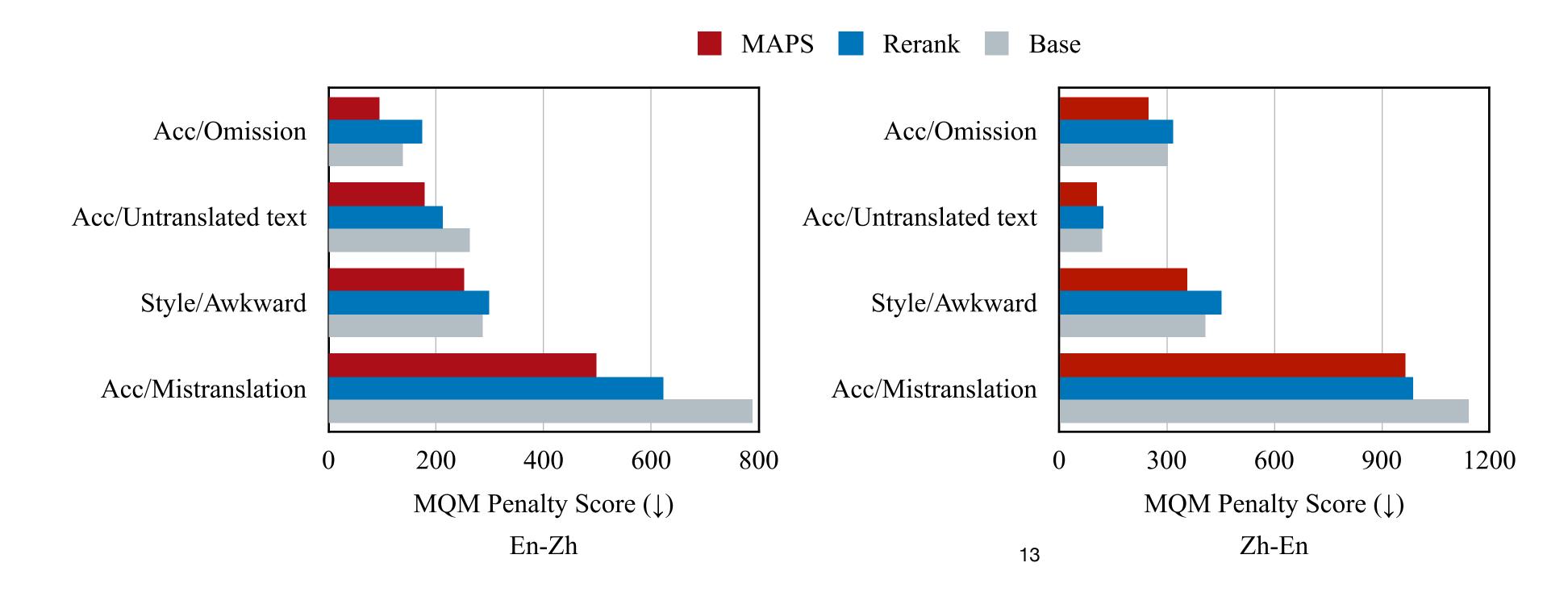
Human evaluation

Multidimensional quality metrics (MQM)

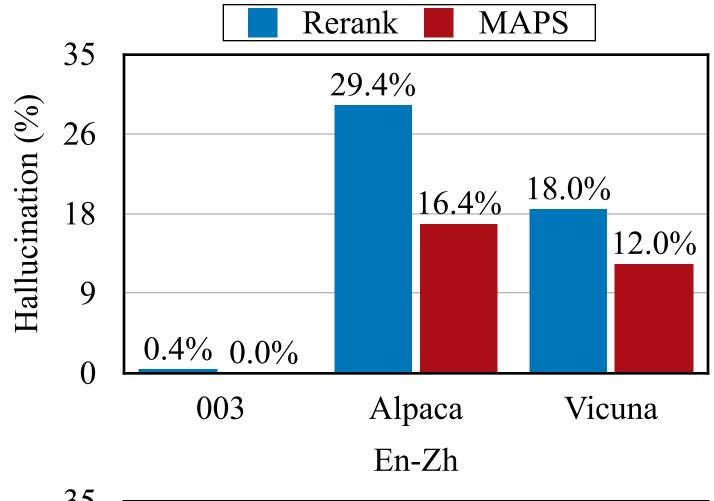
Method	En-Zh	Zh-En		
Base	1.94	2.96		
Rerank	1.79	2.84		
MAPS	1.59	2.60		

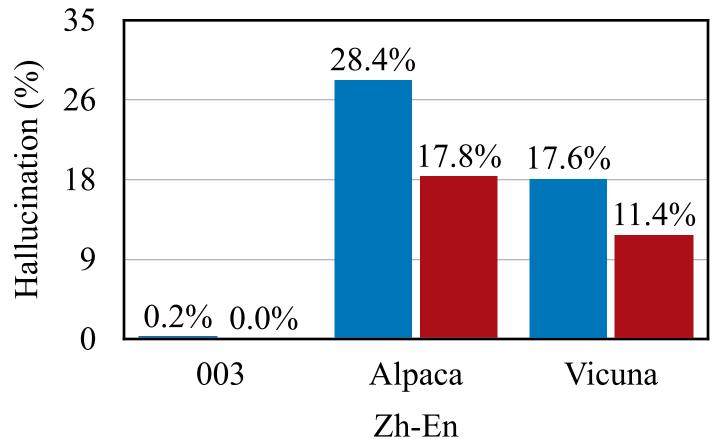
MAPS reduces mistranslation, awkward style, untranslated text, and omission errors.

Table 2: Averaged MQM Score (↓).



Hallucination and Ambiguity





Human-annotated hallucination errors

MAPS reduces LLM's hallucinations

MAPS helps ambiguity resolution

Method	COMET	BLEURT	Accuracy
Rerank	81.5	70.2	61.5
MAPS	82.2	70.6	65.5

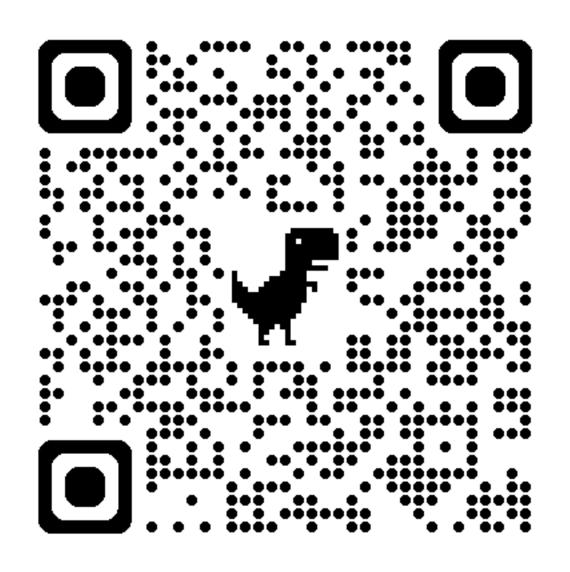
Ambiguity resolution

Using single type of knowledge does not result in consistent improvement

Method	En-Zh	Zh-En	En-De	De-En	En-Ja	Ja-En	De-Fr	Fr-De
			text-day	vinci-003	COMET			
Baseline	86.2	81.6	85.8	85.2	87.9	81.8	82.8	86.3
+Keyword	86.2	81.5	85.5	84.9	88.0	81.5	82.6	86.2
+Topic	86.4	81.7	85.6	85.2	88.1	81.9	83.1	86.3
+Demo	86.9	81.8	86.6	85.2	88.5	81.8	83.4	86.7

- Self-generated knowledge from LLM can be noisy.
- Using multiple knowledge and knowledge selection are important.
- Please refer to the paper for further discussion.

Check our paper & code for more details



Paper



Code